

School of Civil, Environmental and Land Management Engineering Master of Science in Environmental and Land Planning Engineering

A VULNERABILITY ANALYSIS OF THE RED RIVER BASIN, VIETNAM, UNDER CO-VARYING CLIMATE AND SOCIO-ECONOMIC CHANGES

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Abstract

Climate change and socio-economic development are projected to severely impact the hydrological cycle and consequently the water related human activities. Water managers need to account for these future changes in the decision making process to evaluate their expected impacts and identify possible adaptation options. Traditionally, top-down approaches have been used as the basis for developing adaptation strategies, by describing the performance of water resource systems under a discrete set of global projections and focusing mostly on climate change only. In this study, instead, we relies on a bottom-up analysis to identify the major system vulnerabilities with respect to co-varying climate and socio-economic forcings. The Red River basin, Vietnam, is used as a case study as it is a paradigmatic example of many river basins which are experiencing rapid development in terms of population and economic growth, while being exposed to the incoming climate change impacts. The starting point of the study is the generation of co-varying climate and socio-economic scenarios. Time-series of temperature and precipitation are produced by using a semi-parametric weather generator combined with additive and multiplicative scaling factors. They are employed as input for generating the streamflow with an hydrological model. The same scaling factors are used for perturbing temperature and precipitation in the river delta and estimating the agricultural water demand. The water demand scenarios from the other consumption sectors, instead, are generated by multiplying the historical consumptions by other scaling factors. We simulate the Red River model with the current management policy over the generated scenarios to explore their impacts on the system performance. For most of the scenarios, numerical results show a performance degradation compared to the historical one, particularly in terms of supply deficit. We deduced that the large increase of the water demand associated to the fast developing Vietnam society is expected to severely challenge the existing water supply strategies.

Riassunto

I cambiamenti climatici e lo sviluppo socio-economico avranno un forte impatto sul ciclo idrologico e conseguentemente sulle attività umane legate all'acqua. La gestione delle risorse idriche deve considerare questi cambiamenti futuri nei processi di decisione per valutarne gli impatti e identificare possibili opzioni di adattamento. Tradizionalmente, gli approcci top-down sono stati impiegati nello sviluppo di strategie di adattamento, analizzando la performance dei sistemi idrici utilizzando un set discreto di proiezioni climatiche. In questo studio, invece, abbiamo condotto un'analisi bottom-up per identificare le maggiori vulnerabilità del sistema facendo variare contemporaneamente le forzanti climatiche e socio-economiche. Il bacino del Red River, Vietnam, è stato utilizzato come caso di studio essendo un esempio paradigmatico di molti bacini sottoposti ad una rapita crescita demografica ed economica e agli impatti del cambiamento climatico. Il punto di partenza dello studio è la generazione di scenari co-varianti di clima e sviluppo socio-economico. Serie sintetiche di temperature e precipitazione sono state prodotte attraverso un generatore semi-parametrico di clima e attraverso l'applicazione di fattori additivi e moltiplicativi. Queste serie sono state utilizzate nella generazione di afflussi con un modello idrologico. Gli stessi fattori additivi e moltiplicativi hanno permesso di perturbare temperature e precipitazione nel delta del fiume e stimare la domanda idrica per l'agricoltura. Gli scenari di domanda relativi agli altri settori di consumo, invece, sono stati generati moltiplicando i consumi storici per dei fattori di scala. Abbiamo simulato il modello del Red River con l'attuale politica di gestione su tutti gli scenari generati per valutarne gli impatti sulla performance del sistema. Per la maggior parte degli scenari, i risultati mostrano un peggioramento nella performance, se paragonata a quella storica, soprattutto in termini di deficit di fornitura idrica. Ne abbiamo dedotto che il grande incremento nella domanda idrica associato alla rapida crescita che caratterizza la società Vietnamita metterà a dura prova le attuali strategie di fornitura dell'acqua.

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Introduction

1.1 Setting the context

Climate change is considered one of the key drivers of water availability in this century (*IPCC*, 2014). Primary implications are the rise of the mean global temperature and shifts in the precipitation distribution. The hydrological cycle can be highly impacted by these phenomena with serious consequence on water related human activities and ecosystems.

Also the socio-economic and demographic context is rapidly changing. The population is growing and we are observing large migrations from rural areas to the cities, causing increases in water, energy, and food demand, especially in developing countries, where these changes are more emphasized and difficult to contain (*UN*, 2015).

Under these fast evolving conditions, water systems are expected to become increasingly vulnerable, and designing flexible and robust adaptation options, performing well across multiple plausible futures, is key to mitigate degrading perfomance. Large storage systems can play a central role in this changing context by securing water, energy and food production. Yet, the management of these storage systems need to be reconsidered to account for uncertain future drivers. Traditionally, top-down approaches - describing the performance of water resource systems under a discrete set of global projections - have been used as the basis for developing adaptation strategies. Such projections are acquired using general circulation models (GCMs) (*Arnell*, 2004; *Brekke et al.*, 2009), the outputs of which are fed into a water system model to determine the

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system performance with respect to each projection. More recently, bottom-up approaches have been designed to identify performance thresholds independently from global projections. To implement a bottom-up approach, climate (and socio-economic) exposures are generated for a range of plausible futures, including those beyond the bounds of global projections, and system response is assessed against each generated exposure (*Lempert et al.*, 2004; *Prudhomme et al.*, 2010; *Brown et al.*, 2012). This enables a more thorough understanding of how a system responds to changes in climate and society, for example, by identifying the changes in climate exposure that can cause unsatisfactory degradation in system performance (*Whateley et al.*, 2014; *Steinschneider et al.*, 2015).

1.2 Objectives of the thesis

The objective of this thesis is the implementation of a bottom-up, vulnerability analysis of the Red River system, Vietnam, under changing climate and society. The Red River is the second largest river basin in Vietnam, the fifth largest in south east Asia, and is paradigmatic of most river basins in the region, which are experiencing rapid development in terms of population and economic growth (Devienne, 2006), while being exposed to climate change impacts (Giuliani et al., 2016a). The daily operations of the four major reservoirs in the basin have been designed on the basis of the observed hydrologic variability and the historical demands to ensure adequate levels of hydropower production, guarantee water supply for multiple uses in the Red River delta, and mitigate downstream flood, primarily in the capital city Hanoi. Yet, no guarantee exists that the existing operations will not fail in coming years under the additional pressures of the rapid economic and demographic national developments (Toan et al., 2011), along with the expected detrimental effects of climate change (see Arndt et al. (2015) and references therein). Most of the bottom-up analysis are focused only on the climate change effects on the water systems, without considering the socio-economic growth impacts on the water availability and demand, which are projected to be critical in fast developing countries such as Vietnam. The innovative aspect of this thesis is the generation of covarying scenarios of climate and demand that provides a wider point of view on the future vulnerabilities. The starting point of our bottom-up analysis is the generation of a wide range of hydro-climatic and socio-economic scenarios, where the former influence the water availability in the system and the agricultural water demand, while the latter determine the non-agricultural component of the demand (e.g., population, industries, aquaculture). Temperature and precipitation scenarios in the sub-basins are produced by using a semi-

parametric weather generator combined with additive and multiplicative scaling factors. They are successively employed in the streamflow generation with the HBV model. The agricultural water demand in the river delta is obtained by scaling temperature and precipitation as for the upstream sub-catchments and estimating the crop requirement using CROPWAT. The non-agricultural demand scenarios, instead, are generated by producing a set of scaling factors to be multiplied to the historical water consumption of the different sectors. These scenarios are employed in the assessment of the system performance via simulation of an operating policy regulating the four reservoirs in the basin designed over historical conditions. The resulting performance variability across the different scenarios allows identifying the major system vulnerabilities with respect to the co-varying climate and socio-economic forcings. The system vulnerabilities are investigated by comparing the historical performance with the results of the simulation over the generated scenarios with the same management policy to identify which scenarios cause a degradation in the performance. Figure 4.1 shows the main steps of the process which are described in detail in Chapter 4.



Figure 1.1: Outline of the main steps of the study.

1.3 Thesis structure

The thesis is structured in the following parts:

- Chapter 2 provides a review of the literature concerning top-down and bottom-up approaches. We propose a comparison between the two methods with related advantages and disadvantages in order to motivate the adoption the second approach.
- Chapter 3 gives a description of the study site, the Red River system, providing a comprehensive characterization of the territory, the model, and the data available.
- Chapter 4 introduces all the methods and tools adopted for the application of the bottom-up analysis on the Red River basin, mostly focusing on the combination of techniques used in the scenario generation phase for constructing a multi-dimensional exposure space including co-varying climate and socio-economic drivers.
- Chapter 5 shows the numerical results of the analysis. Firstly, the generated scenarios are analysed. In the second part of the chapter, the simulation result are reported and discussed through visual analytics and sensitivity analysis.
- Chapter 6 summarizes the main conclusions and provides some suggestion for improving this work.

2

Literature Review

Water supply infrastructure and operating policies must be designed at timescales for which projections of water availability and demand remain highly uncertain. In order to deal with these changing drivers, two different approaches can be implemented for estimating the impacts and identifying possible adaptive strategies: Top-Down and Bottom-Up approach. Even if these approaches can be applied to many sectors, in this section they are analyzed referring particularly to climate change, since the related literature is more extended and detailed.

2.1 Top-Down Approach

Traditionally, the most used method to assess the impacts of changing drivers on water resources systems is through the downscaling of global scenarios to the local scale (*Wilby and Dessai*, 2010). This approach is called "Scenario-based" or "Top-down" as it moves from global scenarios to local impact assessment. The Top-Down strategy involves a downscaling of the climate variables from Global Climate Models (GCMs), under a range of possible emissions scenarios, to the local scale through the Regional Climate Models (RCMs). The resulting local scenarios are then used to estimate the impacts, as for example the probability of flood events using a rainfall-runoff model or the crop yield using an agricultural model.

2.1.1 Emission scenarios

When climate change is concerned, the starting point of the Scenario-Based methods are the climate scenarios provided by the IPCC (Intergovernmental Panel on Climate Change). Before the Fifth Assessment Report (2014), future climate scenarios were developed and applied with a sequential process: the greenhouse gas emissions and their atmosphere concentrations were estimated, from socioeconomic factors, technology development, and energy production. However, the process lead to some delays among the different stages as the development of the emission scenarios, their implementation in a climate model and the resulting applications in the impacts assessment, due to the linear nature of the causal chain. Experience shows that this full linear process takes about 10 years. To reduce the time gaps and make the information more effective, climate and impact research communities have developed a parallel approach that starts from the identification of radiative forcing scenarios. The radiative forcing scenarios are more effective because they are not associated with unique storylines but can result from different combinations of economic, technological, demographic, political, and institutional futures (Moss et al., 2010).

In the Fifth Assessment Report the scenarios described above are presented as 'Representative Concentration Pathways' (RCPs). In order to avoid the possibility of choosing an average scenario, the number of proposed RCPs is equal to four (see Figure 2.1) instead of an odd number. The numbers in the RCP's names refer to the radiative forcing, measured in watt per square meter, by the year 2100. The grey shaded area captures the 98% (light) and 90% (dark) of the range in the previous socio-economic scenarios.

2.1.2 Global Climate models

The climate scenarios provided by the IPCC are then used to force Global Climate Models. GCMs are mathematical models of the physical processes occurring in atmosphere, ocean, land, ice cover, and the interactions among them. These models rely on a discretization of the Earth in a three dimensional grid, typically having a horizontal resolution between 250 and 600 km. Each cell contains all the interactions among natural and human components (*IPCC*, 2013). However, their temporal and spatial resolutions are quite coarse for the estimation of local impacts related for example to small sub-catchments. Moreover many physical phenomena, such as the clouds or orography, cannot be accurately modeled at this scale (*Wigley et al.*, 1990).



Figure 2.1: Representative Concentration Pathways

2.1.3 From global to local scale

A set of techniques is available to downscale the global models variables to higher resolution (i.e. Regional Climate Models) allowing to capture regional and local climate forcing. These methods can be classified in two main groups: dynamical and statistical downscaling (e.g. *Mearns et al.*, 1999). Dynamical downscaling is also called "nested regional climate modeling" because it implies a nesting of the RCM within the GCM that provides the boundary conditions. In other words, the resolution is increased in the area of interest using the output variables of the GCM as drivers (*Giorgi*, 1990).

The main shortcomings of this approach are the high computational time, the dependency of the quality of the regional model control run on the quality of the GCM boundary conditions, and the need of tuning the parameters when applied to new regions (*Mearns et al.*, 1999). Additionally, it was proved that the outputs of the regional models are subject to varying levels of systematic biases and they need to be post processed before being used for climate impact assessment (e.g. *Christensen et al.*, 2008).

Statistical downscaling, instead, is an empirical approach that uses relationships between the observed local and large scale data to increase the resolution of the climatic variables. The relationship is a function calibrated to map global variables into their corresponding local variables and it can be implemented as follows:

$$R = f(L) \tag{2.1}$$

where L represents the predictor (i.e. large-scale climate variables), R is the predictand (i.e. regional scale variables) and f is a deterministic/stochastic

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Figure 2.2: The different stages of the bottom up process.

function that is calibrated with observed data of L and R (e.g. *Coulibaly et al.*, 2005). Once the function f is estimated, it can be used for predictions of the future climate variables under the strong assumptions that this relationship will remain valid in the future and the predictor L will remain within the range observed in the calibration period.

Beside the dynamic and statistical methods, the downscaling procedure can be achieved with a third option called combined downscaling, which is a combination of the two methods described above. The output of the dynamical downscaling, the RCM variables, are corrected using a statistical transformation calibrated as in equation 2.1 (e.g. *Piani et al.*, 2010), but instead of using the large scale observed data (*L*) as the predictor, the RCM outputs are employed. Once the climatic variables have an acceptable resolutions, they can be used for the calculation of the impacts at the local scale.

2.2 Bottom-Up Approach

In recent years another method has been developed to estimate impacts and related adaptation options independently from climate projections. This approach is named 'Vulnerability-Based' or 'Bottom-up' approach, which relies on the idea of identifying the vulnerabilities of a system by assessing its performance under a range of plausible changes in climate, potentially including also the ones downscaled from the GCMs (*Lempert et al.*, 2004; *Brown et al.*, 2012). The name 'Bottom-up' reflects the differences in the sequential process with respect to the Top-Down approach which implies a transition from the global emission scenarios to the local scale impacts. Here, on the other hand, the starting point is to analyse the historical local climate conditions in order to under-

stand in which case the water system failed and could have been managed differently (*Wilby and Dessai*, 2010). After that, a sampling of the climate variables is generated starting from the historical series and the system is tested on each sample to understand which scenarios lead to a degradation in the system performance. Generally, a failure threshold is used to classify the performance in acceptable or failures. When the performance becomes unacceptable, they can be improved by designing different planning or management strategies (*Jones*, 2001; *Culley et al.*, 2016).

2.2.1 Historical data analysis

The first step of the bottom-up approach is the analysis of the historical system performance to understand the main vulnerabilities and, possibly, to identify critical thresholds for the system performance.

For example, if the main goal is to avoid floods in the area of interest, one can identify the climate conditions in past years that have led to floods and the related water height that caused the damages. Assuming that the stakeholders don't want to exceed certain damage costs, the threshold becomes the maximum acceptable height above which the system can be considered in failure (*Brown et al.*, 2012).

2.2.2 Exposure space

A set of plausible future scenarios are generated by altering the historical variable of interest in the so called 'exposure space' (step 1, Figure 2.2). Each point of the space is a scenario produced by increasing or decreasing the variables on the axes starting from the historical values which are represented in the origin. The space is *n*-dimensional, where *n* is the number of variables ($\theta_1...\theta_n$) describing the scenarios (*Culley et al.*, 2016). Although, the variables are often temperature and precipitation in climate change applications, also other factors can be involved, like evapotranspiration or socio-economic related variables as water demand or energy price. The selection process of these variables is crucial for the effectiveness of the study because they should be those to which the system is more sensitive (*Mastrandrea et al.*, 2010).

Sensitivity Analysis (SA) can contribute to the identification of the variables that most influence the system performance through a three-step process: the sampling of the variables in their domain, the evaluation of the model output with the generated samples and the estimation of indices that provide the effect

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of a change in the input on the output (Saltelli et al., 2008).

Once the variables are selected, the exposure space needs to be filled up perturbing the historical values of the variables. The most common ways to generate scenarios are the additive and multiplicative methods; they consist in simply adding or multiplying the past data by a scaling factor Δ that changes the time series values or the statistics related to them (*Prudhomme et al.*, 2010). However, the resulting scenarios show the same pattern as the historical one, without taking into account shifts in long term precipitation persistence and extreme events (*Steinschneider and Brown*, 2013) which could happen in future under climate change (*Solomon*, 2007).

Alternative and more sophisticated approaches can be implemented to include multiple temporal scale behaviour. Stochastic weather generators, for example, allows generating synthetic series of data that are strictly conditioned to their historical features but at the same time, they can introduce differences in the intensity and frequency of daily precipitation (*Steinschneider and Brown*, 2013).

2.2.3 Failure boundary

The model of the system is simulated under each scenario generated using the current historical management. The performance associated to each scenario is represented in the exposure space and can classified in "success" and "failure" based on the failure threshold established in the first analysis. The space is subdivided into regions of acceptable performance and others where the changed climate leads to a degradation in the system performance to the point that the values of the considered objectives, are below the thresholds (*Whateley et al.,* 2014). The limit between the two regions is called "failure boundary" (step 2, Figure 2.2).

In order to improve the system performance and get satisfactory values of the objectives it is possible to search for adaptation options for each failure point of the exposure space. After the optimization process, more points of the space are classified as "success" and consequently the failure boundary is enlarged (step 3, Figure 2.2). The ratio between the number of successful scenarios after the optimisation and the number of the successful scenarios related to the historical management is called maximum adaptive capacity and represents the ability of the system to handle the changing drivers (*Culley et al.*, 2016).

2.2.4 Superimposition of climate projections

The last step of the bottom-up approach is the projection of the global scenarios into the exposure space (*Whateley et al.*, 2014) (step 4, Figure 2.2). This link



Figure 2.3: Comparison between the stages of Top-Down and Bottom-Up approaches

between Top-down and Bottom-up approach provides a clear overview of the "position" of the official scenarios compared to the failure boundary and gives an idea on the temporal evolution of the expected future climate.

2.3 Top-Down VS Bottom-Up

It is well known that the future changes in climate, socio-economic and technological development have to be considered and modeled in the decision making process of the water systems (*Brown et al.*, 2012).

The two approaches previously described aim to help the water resource managers in estimating future impacts and possible adaptation options to these changes. Top-Down and Bottom-Up methods imply different processes and techniques as illustrated in Figure 2.3.

The top-down approach has been studied and used in the water management field for many years. It provides impact projections under official scenarios and it often used for strategic planning. In addition, this IPCC approach is the most widely adopted approach in the scientific literature (*Wilby and Dessai*, 2010).

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Figure 2.4: The envelope of the uncertainty: the increasing number of triangles at each level symbolise the growing number of permutation and hence the expanding envelope of uncertainty (taken from Wilby and Dessai (2010)).

The most recognized limitation of this method is the expansion of the uncertainty at each step of the process. This happens because the information is cascaded from one step to the next and at each step there is a range of possible models and methods that can be chosen by the user. Firstly one must select a global scenarios between the RCPs provided by the IPCC, then select a GCM within a large variety of models developed by different climate institutes. The GCM's resolution must be increased with different methods of dynamical, statistical, or combined downscaling to get the corrected RCM variables, but also the choice of the RCM is subject to uncertainty. Lastly, the local impact model must be selected, within a large range of possible choices (Prudhomme et al., 2010). In short, every choice at each step implies different results on the impacts and consequently on the adaptation strategies. Depending on the selection of GCM, RCM or the downscaling technique, the impacts might be divergent, in one way minimal, in another way very dangerous for the system (Brown et al., 2011). This effect is known as envelope of the uncertainty and is illustrated in Figure 2.4.

The second shortcoming of the Scenario Based implementation is the discrete set of scenarios explored by the approach. If the researchers analyse exclusively the climate projections, the future variable space under climate change may not be fully explored, and consequently the model range would lead to a partial estimation of future impacts (*Brown and Wilby*, 2012). It thus represents the lower bound on the maximum range of uncertainty (*Stainforth et al.*, 2007). Moreover, the limitation due to the discrete number of scenarios doesn't allow to identify

the acceptance or refusal thresholds of the system performance under changes in climate. In other words, using the top-down approach, the degree of climate change to which the system is more sensitive are very difficult to find (*Culley et al.*, 2016).

The bottom-up approach has been developed to solve some of these limitations using a different starting point and avoiding the expansion of the uncertainty. Furthermore, the ability to evaluate the adaptation capacity is a great improvement for the system flexibility assessment. However, even the new approach provides difficulties and uncertainties, from the exposure space generation to the choice of the failure threshold. The impacts on the system and the adaptive management strategies can be fully explored only if the exposure space provides the best range of plausible future changes and if the failure threshold has been correctly assessed. Some techniques are available to improve the approach implementation. For example, the set of methods called "scenario discovery" aims to find the drivers causing failure in the system under specific future states of the world (*Kasprzyk et al.*, 2013).

3

The Red River system

This study is focused on the water management vulnerabilities of the Red River system in northern Vietnam.

This is a paradigmatic example of fast developing countries which are currently undergoing a rapid economic and demographic development characterized by internal migrations from rural areas to the main cities. Population growth leads to increases in water, food, and energy demands. This factor, combined with the climate change effects on the global hydrologic cycle, is expected to have serious consequences on the water availability (*McDonald et al.*, 2011).

In Vietnam, the liberalization of economic production and exchange in the last 30 years has led to an explosive economic and demographic development (*Toan et al.*, 2011). The energy demand has increased with a 15% annual rate in the last ten years, intensified by the migration of the rural population to the main cities that are sprawling uncontrolled (*Vinh Hung et al.*, 2010). Climate change, with its projected impacts on the water cycle, could affect two important sectors for the national economy, hydropower production and agriculture. Hydropower is the primary renewable energy and agriculture is a key driver for the local food supply and the international trading. Both sectors are strictly related to energy and food security.

Large storage projects have increased water availability for different economic sectors, but the existing storages' management strategies have to be reconsidered for enhancing the flexibility and the adaptive capacity of the water systems under future changes (*Georgakakos et al.*, 2012).



Figure 3.1: The Red River system map.

3.1 The Red River Basin

The Red River is a transnational river basin, located in South-East Asia, covering an area of 169,000 km² and flowing through 3 countries: Vietnam, China and Laos. The part in Vietnam territory covers 25 provinces and cities with the total area of 86,700 km², accounts for 51.3% of the basin area. The parts located in China and Laos are $81,200 \text{ km}^2$ (48 % of the basin area) and $1,100 \text{ km}^2$ (0.7%of the basin area) respectively (Dinh, 2015). The Red River is the second biggest river in Vietnam, after Mekong. It is formed by 3 main tributaries: Da river on the right, Thao river in the middle, and Lo river on the left, as shown in Figure 3.1. Among the tributaries, Da is the largest one in term of water flow since it contributes approximate with the 49% to the total flow. The Red River basin is characterized by a sub-tropical monsoon climate that implies a wet and a dry season. The wet season lasts from May to October cumulating 85-95% of the total yearly rainfall (Le et al., 2007). The average river flow at the measure station of Son Tay varies between 8000 m^3/s during the monsoon peak and 1500 m^3/s in the dry months. The available water in the basin is quite abundant but, unfortunately, these plentiful sources are not evenly distributed in terms of space and time. This uneven distribution causes serious effects on livelihoods of local people such as water deficit for irrigation and domestic uses.

Many reservoirs have been being built, both in China and Vietnam territory

with the aims of hydropower generation, water supply, and food control. As we saw, 48% of the Red River belongs to China and information about this area are scarce. Recently, China strongly exploit the water resources by constructing series of reservoirs for generating hydropower. These reservoirs have been mainly built since 2007 with the total capacity of more than 4 billion m³. Most of them are medium size and they are mainly located upstream of the Da sub-basin. However, the information about these reservoirs and hydropower plants such as location, storage capacity, water usages, or operating rules is insufficient and in many cases not available. Hence it causes certain difficulties for Vietnam to plan/manage efficiently water resource as well as regulate the reservoirs within the Vietnamese territory. For example, during the flooding season (generally from June to November), the reservoirs in China part, who do not concern with flood control, usually store water from middle June to July to aim at reaching their fullest capacity in the early flood season in order to maximize hydropower production. Therefore, if the floods come, they have to release a larger flow (compared to the inflow to those reservoirs) for their safety. As a consequence, the capacity of reservoirs in Vietnam for flood control will reduce having a serious risk of damages in the city of Hanoi.

In Vietnam territory, several reservoirs have been built and operated since the 70s. They play an important role not only in hydropower production but also in flood control and water supply for irrigation, domestic use, and industries in the river delta.

On the Da river, two large multi-purpose reservoirs were constructed, Son La and Hoa Binh, while another reservoir, Lai Chau, is under construction.

Son La was built in 2005 and started operating in 2010. The maximum water level in the reservoir is 228.07 m and the corresponding storage is 12,457 billion m³. The Son La hydropower plant is the biggest in Vietnam in term of power generation with a total design capacity of 2,400 MW. Hoa Binh reservoir started operating in 1991. Its has a maximum water level of 122 m and a storage capacity of 10.89 m³. The Hoa Binh hydopower plant has eight turbines for a total design capacity of 1,920 MW.

Besides the Da river reservoir, Thac Ba and Tuyen Quang are the two largest reservoir on the Lo tributaries, Chay and Gam river respectively. Thac Ba was the first hydropower station in the North Vietnam (1971), with 61 m of level and 3,643 billion m³ of maximum storage. Its hydropower plant has a total capacity of 120 MW. Tuyen Quang, instead, was constructed later (2008) with a storage capacity of 2.482 billion m³ and a total design capacity of the turbines of 342 MW.

Additionally, there are about 13,000 small size reservoirs, dams, and pumping

3. The Red River system

station built for irrigation purposes within the basin. They affect the system hydropower and supply only locally without having considerable influence on the water resources management of the delta.

The delta region covers 11 provinces and cities, including the capital city of Hanoi. With the total population living in the delta equal to 20,236 million people, it is the highest population density in Vietnam. More than half of the delta is less than 2 meters above mean sea level. It is protected from flooding and storm surges by a system of river and sea dykes.

The region is mainly cultivated with rice and the irrigation relies on a combination of gravity and pumping systems. Agriculture is the bigger water user accounting for the 76% of the total used water and it involves around 50% of the local workers. The river delta is the second largest rice production area of Vietnam, which is, in turn, the second largest rice exporter in the world (*Yu et al.*, 2010). The other consumption sectors include domestic use, aquaculture, industries, and livestocks. For these reasons, the delta has an important role in terms of food security and socio-economic development.

3.2 Model and data

This section provides an overview of the Red River model developed within the IMRR Project (Integrated and sustainable water Management of Red-Thai Binh River System in a changing climate) (*Bernardi et al.*, 2014; *Dinh*, 2015; *Giuliani et al.*, 2016a). The Red River system has been modeled as a combination of conceptual and data-driven models assuming a time-step of 24 h for modeling and decision-making processes. In Figure 3.2, each modeled unit is represented with the corresponding inputs, state variables, and outputs. In the next subsections, these models and dynamics are described in detail.

3.2.1 The sub-catchments

The five river basins, Da, Lo, Gam, Chay, and Thao, are described with conceptual HBV models. This model simulates the soil water balance and subsequently the rainfall-runoff process. It takes as inputs historical temperature, precipitation, and streamflow trajectories to calibrate 12 parameters (see section 4.3 for a detailed description of the model).

The daily discharges, q_t^1 , q_t^2 , q_t^3 , q_t^4 , q_t^5 , are obtained as a function of daily temperature and precipitation related to each sub-catchment. The precipitation data used for the calibration of the sub-catchment models are produced within the APHRODITE project (Research Institute for Humanity and Nature, Japan)



Figure 3.2: Representation of the Red River system model

(*Yatagai et al.*, 2012), due to the scarcity of data available for the upper parts of the basins located in China. Historical daily temperature, precipitation, and streamflow observations for each sub-basin are represented in Figure 3.3, 3.4, and 3.5 respectively. In particular, the streamflows are measured at the time they flow into the reservoirs, except for Lo and Thao which are measured at Ham Yen and Yen Bai respectively.

In all the sub-basins, the maximum temperature is between 24 and 27 degrees, while the minimum varies between 3 and 6. The monsoon season is clearly visible on both precipitation and streamflow patterns in the period from May (day 120) to October (day 273), where the amount of water is considerably higher. From the streamflow graph it is easy to recognize which are the tributaries that have a grater contribution to the river flow. Particularly, Da and Thao river identified by the orange and green lines respectively, show a considerably higher levels compared to the other rivers streamflows.



Figure 3.3: Temperature in the Red River sub-catchments (1961-1963)



Figure 3.4: Precipitation in the Red River sub-catchments (1961-1963)


Figure 3.5: Streamflow of the Red River tributaries (1961-1963)

3.2.2 The reservoirs

The water volume of a reservoir at time t + 1, x_{t+1} [m^3], is a function of the water volume at the previous time x_t , the inflow, the evaporated volume, and the volume released with regulated gates and spillways (equation 3.1).

$$x_{t+1} = x_t + a_{t+1} - r_{t+1} - E_{t+1}$$
(3.1)

The inflow $a_{t+1} [m^3/d]$, is the cumulative water volume of the tributaries, the distributed runoff along its banks, and the direct precipitation on the water surface. The evaporated volume $E_{t+1} [m^3/d]$, is proportional to the area of the water surface and the specific daily evaporation rate (equation 3.2).

$$E_{t+1} = e_{t+1}S(x_t) \tag{3.2}$$

where the surface $S_t [m^2]$ is a function of the storage x_t and the specific evaporation $e_{t+1} [m/d]$ depends on a complex multitude of factors (water and air temperature, relative humidity, atmospheric pressure, etc.). Finally, $r_{t+1} [m^3/d]$ is the volume released in the interval [t, t+1) through penstocks, gates, and spillways.

The control variable is the release decision u_t , which coincides with r_{t+1} only when the spillways and the bottom gates are not operating. The relationship between u_t and r_{t+1} is formalized as follows:

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Figure 3.6: The minimum (green) and maximum (blue) release discharge curves of the Hoa Binh reservoir.

$$r_{t+1} = R(x_t, u_t, a_{t+1}, e_{t+1})$$
(3.3)

The release function *R* is the most complicated relationship to identify, because the release process is continuous in the time interval [t, t + 1), but the effects need to be described with a time-discrete model. The values of the instantaneous inflows and the evaporation rate trajectories are never known in practice, therefore they have to be assumed constant in every time step. Under this assumption, the release function has been built as follows:

$$r_{t+1} = R(x_t, u_t, a_{t+1}, e_{t+1}) = \begin{cases} v_t(x_t, a_{t+1}, e_{t+1}) & \text{if } u_t < v_t(x_t, a_{t+1}, e_{t+1}) \\ V_t(x_t, a_{t+1}, e_{t+1}) & \text{if } u_t < V_t(x_t, a_{t+1}, e_{t+1}) \\ u_t & \text{otherwise} \end{cases}$$
(3.4)

Where $v(\cdot)$ and $V(\cdot)$ are the minimum and maximum releases, defined assuming the regulation gates completely close or open and accounting for possible spillways. In Figure 3.6, the curves of minimum and maximum releases are shown as an example for the Hoa Binh reservoir.

Each reservoir is connected to a multi-turbines hydropower plant. In these plants, each turbine can be independently activated with the desired flow because each of them is fed by an independent penstock controlled by a valve.



Figure 3.7: Daily energy production in the Hoa Binh power plant as a combination of daily release and *level*

The daily maximum energy production of each plant can be estimated as a function of the daily water volume released from the reservoir, the reservoir level, and the specific features of the installed turbines such as the hydraulic capacity or the head loss functions. This relationship is estimated assuming that the operator choose the optimal allocation of the releases among the turbine in different hours of the day. Using this relationship, for each combination of released volume and reservoir level, the energy that can be produced in each power plant can be obtained as shown in Figure 3.7 for the Hoa Binh reservoir.

3.2.3 The delta

The reservoir releases and the natural streamflow of Thao and Lo rivers flow downstream and reach the city of Hanoi and the irrigation districts in the river delta. The river delta was originally described by a 1D hydrodynamic model (MIKE11) that considered the water flow in 907 rivers and canals forming the delta river network. It includes also the description of structures within the Delta, such as bridges and pumping stations. This model is based on the observations measured in 5000 cross sections on 4200 km of canals, registered during two monitoring campaigns in 1999-2000 and 2009-2012. MIKE11 is a very accurate and spatial distributed description of the delta dynamics but it is also highly computational expensive (i.e., it takes 2 days for simulating 16 years). Due to the impossibility of using MIKE11 for the policy design process, that

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requires an high number of simulations, dynamic emulators were developed to simplify the canals dynamics and consequently reduce the computational time.

The emulation model is constituted by recursive Artificial Neural Networks trained over the results of the De Saint Venant equations and it reproduces the outputs needed for the objective calculation. Due to the large number of input variables needed by MIKE11, before training the ANN, the most representing variable were selected by using the Iterative Input Variable Selection (*Galelli and Castelletti*, 2013) algorithm which provided an accurate model dependent on few variables. The calibration of the ANN has been carried out on dataset including 62 years of daily values.

The resulting models provide approximate values of the spatially distributed volume of water available in the irrigation canals (CWV_t) and the water level in Hanoi (z_t^{HN}). Their formulations are shown in equation 3.5 and 3.6.

$$CWV_{t+1} = f(CWV_t, q_{t+1}^{delta}, W_t, \tau_{t-1})$$
(3.5)

$$z_{t+1}^{HN} = f(z_t^{HN}, q_{t+1}^{delta}, \tau_{t-1})$$
(3.6)

with

$$q_{t+1}^{delta} = q_t^{ST} - q_t^{DD} \tag{3.7}$$

Where q_{t+1}^{delta} describes the difference between the water in Son Tay ($q_t^{ST} = r_t^2 + q_t^2 + r_t^3 + q_t^4 + r_t^4$ see Figure 3.2) and the potential diversion of water in the Day diversion (q_t^{DD}), accounting for the time delay between Son Tay and the delta. The Day diversion is used only in the case where there is a risk of flood events in Hanoi. τ_{t-1} is the tide level at the previous day that accounts for the seawater intrusion in the delta. W_t is the daily water demand of the Red River districts calculated as the sum of all the water sector demands. The considered sectors are: agriculture, aquaculture, industries, population (urban, town, rural), and livestocks (Figure 3.8).

3.3 Formulation of the objectives

According to a direct interaction with the stakeholders, the main water-related interests to be considered in the policy design process are hydropower production, flood control, and water supply. The objective function vector, to be minimize on the simulated horizon H, is $J = |-J^{hyd}J^{flood}J^{supply}|$.



Figure 3.8: Temporal pattern of the monthly water demand

Concerning the first objective, the daily average energy production, to be maximize, is defined as

$$J^{hyd} = 1/H \sum_{t=0}^{H-1} HP_{t+1}$$
(3.8)

where HP_{t+1} is the hydropower production (example in Figure 3.7 for the Hoa Binh reservoir), which is estimated simulating the optimal hourly operation of the turbines given the net hydraulic head and the daily reservoir volume. The net hydraulic head is the difference between the reservoir level and the tailwater level.

The flood control problem is solved minimizing a damage objective function which has to be minimized. The daily average flood damage in Hanoi is estimated by a dimensionless non-linear cost function (Figure 3.9) which has been defined by consulting the local experts (i.e. Flood Commission) and it depends on the water level in Hanoi (equation 3.6):

$$J^{flood} = 1/H \sum_{t=0}^{H-1} F(h_{t+1}^{HN}) = \begin{cases} 0 & \text{if } h_{t+1}^{HN} < 0.6 \\ (h_{t+1}^{HN} - 6) \cdot 750000/5.25 & \text{if } h_{t+1}^{HN} < 11.25 \\ 1.51 \cdot 10^6 (h_{t+1}^{HN})^4 - 7.00 \cdot 10^7 (h_{t+1}^{HN})^3 + \\ +1.22 \cdot 10^9 (h_{t+1}^{HN})^2 - 9.45 \cdot 10^6 (h_{t+1}^{HN}) \\ +2.74 \cdot 10^{10} & \text{otherwise} \end{cases}$$
(3.9)



Figure 3.9: Non linear function for the estimation of the damage cost of floods in Hanoi

Finally, the objective related to the water supply is calculated as the daily average squared water deficit with respect to the total water demand of the Red River delta. As the delta model described before, the water distribution process in the delta region is approximated with a data-driven artificial neural network (ANN).

$$J^{supply} = 1/H \sum_{t=0}^{H-1} (ANN(q_{t+1}^{delta}, W_t, tide_{t-1}, CWV_t))^2$$
(3.10)

This ANN model is a non-dynamic surrogate model that approximates the water deficit obtained with MIKE11 that provides a detailed description of each canal dynamic but it is highly computational expensive, as described in section 3.2.3. The quadratic formulation has been adopted for the penalization of serious deficits, which allowing for small and frequent deficit.

3.4 Policy design

The set of optimal operating policies has been designed via Evolutionary Multiobjective Direct Policy Search (EMODPS). It is a simulation-based optimization approach that combines direct policy search, non linear approximating networks, and multi-objective evolutionary algorithms to design Pareto-approximate closed-loop operating policies for multipurpose water reservoirs (*Giuliani et al.*, 2016b). The decision vector is composed by the release decision of each reservoir which is a function of the day of the year *t*, the reservoir storage $(x_t^1, x_t^2, x_t^3, x_t^4)$, and the total previous day inflow $(q_t^1 + q_t^2 + q_t^3 + q_t^4 + q_t^5)$:

$$\mathbf{u}_{t} = |u_{t}^{1} \quad u_{t}^{2} \quad u_{t}^{3} \quad u_{t}^{4}| \tag{3.11}$$

EMODPS is based on the parametrization of the operating policy p_{θ} . The parameter space Θ is explored to find the parametrized policy that optimizes the expected long term cost, i.e.

$$p_{\theta}^* = \arg\min_{p_{\theta}} J_{p_{\theta}} \quad \text{s.t.} \theta \in \Theta$$
(3.12)

Where *J* is the objective vector defined in section 3.3.

The parametrization of the policy is implemented with Gaussian radial basis functions (RBFs) which allow to approximate the unknown solution to any desired degree of accuracy. They were demonstrated to be more effective than other non-linear approximating networks (*Giuliani et al.*, 2014).

The optimization of the policy parameters was implemented using multi-master Borg MOEA (*Hadka and Reed*, 2013). Multi-objective evolutionary algorithms (MOEAs) are iterative search algorithms inspired by the process of natural evolution that evolves a Pareto-approximate set of solutions. Borg MOEA employs multiple search operators that are adaptively selected during the optimization. Borg is demonstrated to be highly robust in solving different multi-objective problems making it very useful for the EMODPS problems, where the policy parametrization is completely unknown a priori.

4

Methods and tools

This section aims to provide an overview of all the methods involved in the application of the Bottom-up approach on the Red River system. Figure 4.1 provides a schematic representation of the main steps of the study. The generation of the climate scenarios at the top-left corner is the starting point for the generation of new weather trajectories (p^H, t^H) and the agricultural water demand (W^A) . On the other side, socio-economic scenarios are generated to estimate the demand related to other water consumption sectors (W^{NA}). The weather scenarios are simulated in the hydrological model to obtain each sub-catchments streamflow (q^H) needed as inputs for the reservoir and power plant models (section 3.2.2). The water demand scenarios, instead, are aggregated (W^{TOT}) and employed in the delta model described in section 3.2.3. Finally, using the comprise policy, the Red River model is simulated over each scenarios to estimate the values of the three objectives (J^{HYD} , J^{FLO} , J^{SUPPLY}). With reference to the Bottom-up framework previously described, the red and blue boxes represent the generation of the exposure space while the green box corresponds to the simulation of the system and the evaluation of its performance under the exposure scenarios. The results were analyzed implementing a Sensitivity Analysis between the input scenarios and the resulting objectives. Moreover, the official projections of future climate were downscaled and used as input for the system performance evaluation to have an idea of the position of the scenarios with respect to the generated ones. In the next sections, the methods used in each step of the process are described in detail.



Figure 4.1: Outline of the main steps of the study.

4.1 Climate and socio-economic scenario generation

As in most bottom-up studies (e.g. *Brown et al.*, 2012; *Culley et al.*, 2016) the climate scenarios of temperature and precipitation are generated by applying additive and multiplicative factors (Δ^T , Δ^P) on the historical observed means. We chose the following vector of factors to be multiplied to precipitation:

$$\Delta^P = \begin{bmatrix} 0.8 & 0.9 & 1.1 & 1.2 & 1.3 & 1.4 & 1.5 & 1.6 \end{bmatrix}$$
(4.1)

Applying this vector to the observed average is equivalent to alter the precipitation amount from - 20% to + 60%.

Regarding temperature, we chose an additive perturbation with a vector defined by the following factors:

$$\Delta^{T} = \begin{bmatrix} -2 & -1 & +1 & +2 & +3 & +4 & +5 \end{bmatrix} (^{\circ}C)$$
(4.2)

The Δ ranges were chosen in order to provide a large variability in both positive and negative directions, considering also values that are probably unlikely to



Figure 4.2: Latin Hypercube sampling of the scaling factors for the water consumption sectors

realize in future. In addition, we take into account the downscaled climate projections by IPCC which predict increases in temperature and precipitation which are within the considered domains. A similar technique is employed to generate socio-economic scenarios, except for the agricultural ones which we assumed that are influenced only by the climate conditions. We chose a wide range of scaling factors to be multiplied to each water consumption sectors, including the projections of the future socio-economic development produced by the Vietnamese authorities. Within these ranges, we generate 100 samples with the Latin Hypercube method.¹

The sampled factors (Δ^W) are illustrated in Figure 4.2. Each point represents the percentage factor to be added to the actual consumption of the corresponding sector.

4.2 Weather generation

The additive and multiplicative factors (Δ^T, Δ^P) from the previous step are subsequently employed in the weather generation. Because of the disadvantages explained in section 2.2.2, the factors are not simply added to the historical mean but, instead, we produced new synthetic series of temperature and precipitation using a semi-parametric weather generator.

¹The Latin Hypercube sampling is a statistical technique for generating near-random sample of parameters values from a multidimensional distribution. This method implies the stratification of the variable domain in equiprobable intervals and the sample are selected from each interval (*McKay et al.*, 1979).

Weather generators are statistical models calibrated over observed daily weather sequences. They are useful when the meteorological data are insufficient in terms of their time and spatial coverage or, as in this case, for the generation of future climate scenarios. They implies the simulation of the main statistics of the observed records, as for example mean, variance or extremes, to produce synthetic series (*Wilks and Wilby*, 1999).

Weather generators can be classified in three main categories: parametric, nonparametric, and semi-parametric. Parametric generators assume that the weather characteristics can be described by a known distribution, where the parameters are estimated from the historical records. Non-parametric methods, on the other hand, don't assume any distribution and they rely on a resampling of the historical data to generate synthetic series. Finally, the combination of the two methods is called a semi-parametric generator.

4.2.1 Parametric weather generators

Parametric generators typically use precipitation as the driving variable while the maximum and minimum temperature along with the solar radiation are generated according to the occurrence of precipitation values previously produced. The model preserves the temporal dependence, the correlation between variables and the seasonal characteristics of the actual weather in a certain location (*Richardson*, 1981).

A first-order Markov Chain is often used to generate a sequence of wet and dry days where the difference is defined by a certain threshold. Denoting a wet day at time t as W_t and a dry day as D_t , the probabilities of transition from a wet day to a dry day or vice versa are defined as:

$$P(W_{t+1}|D_t) = (\text{#of dry days followed by a wet day})/(\text{#of dry days})$$
 (4.3)

$$P(W_{t+1}|W_t) = (\text{#of wet days followed by a wet day})/(\text{#of wet days})$$
 (4.4)

And by the law of total probability:

$$P(D_{t+1}|D_t) = 1 - P(W_{t+1}|Dt)$$
(4.5)

$$P(D_{t+1}|W_t) = 1 - P(W_{t+1}|Wt)$$
(4.6)

Once the Markov chain is costructed, the amount of rainfall must be associated to the wet days. This amount can be generated from an exponential distribution, which is described only by one parameter λ (*Richardson*, 1981). Alternatively, a Gamma distribution (two parameters) can be used (e.g. *Katz*, 1977; *Wilks*, 1989), but other authors find the mixed exponential distribution working better (e.g. *Lettenmaier*, 1987; *Wilks*, 1998; *Woolhiser et al.*, 1982). The mixed exponential distribution is a weighted average of two exponential distributions and implies the evaluation of three parameters:

$$f(x) = \alpha \lambda_1 \exp(-\lambda_1 x) + (1 - \alpha_2) \exp(-\lambda_2 x)$$
(4.7)

After generating the occurrence and the amount of rainfall, the daily maximum and minimum temperature and the solar radiation can be conditioned to the occurrence of precipitation. Temperature and solar radiation are not independent, they are correlated with each other and with precipitation. In order to consider this dependency, a first-order auto-regression vector, VAR(1), is fitted by calculating the residuals of temperature and radiation.

The residuals are obtained by removing the signal from the historical series, subtracting the mean and dividing by the standard deviation. The VAR(1) process is defined as:

$$z(t-1) = Az(t-1) + B\epsilon(t)$$
(4.8)

where z(t) and z(t-1) are the vectors (3X1) of the residuals of maximum temperature, minimum temperature, and solar radiation at time t and t - 1, $\epsilon(t)$ is the vector (3X1) of independent standard normal random variables at time t; A and B are the matrices (3X3) describing the auto and cross-correlation between the time series and they are calculated as the covariance matrix of the variables, S, and the same matrix lagged by one step, S^{-1} , i.e.

$$A = S_1 S^{-1} (4.9)$$

$$BB^T = S - AS_1^T \tag{4.10}$$

Parametric generators are easy to implement but involve some drawbacks (*Api-pattanavis et al.*, 2007). For example, VAR models require normality of the data and if they don't meet this condition, they have to be transformed with a quite difficult process and the model performance in the transformed space is not

guaranteed. Moreover, for the rainfall amounts, some features of the data cannot be captured by the probability density function of the mixed exponential distribution.

4.2.2 Non-parametric weather generators

In the literature, several techniques are proposed for non-parametric weather generation, such as simulation from empirical distribution of wet and dry spells and precipitation amount, neural networks for generating temperature, the use of simulated annealing for generating precipitation.

The easier version of this set of methods is the simple bootstrap, which implies a generation of a new weather sequence through independently resampling (with replacement) of the historical records (*Efron*, 1979; *Efron and Tibshirani*, 1994). The inability of keeping the correlation between the observations is the main shortcoming of this method. This limit is partially solved using a similar approach called moving-block bootstrap (*Vogel and Shallcross*, 1996). The generation, in this case, is implemented by resampling blocks of consecutive values so that the correlation is preserved inside each block. Yet It is not mantained among the blocks.

The k-nearest-neighbor (k-nn) bootstrap, instead, is an alternative method that can reproduce the autocorrelation between each value (*Lall and Sharma*, 1996). The historical record is divided into blocks of length d, which represents the dependency between the observed values. For example, if d is equal to 2, each value depends on the previous two. Starting from one random block in the historical period, the next one is generated choosing the block, in the records, that is the nearest compared to the others. In order to find the nearest, all the blocks are classified by a distance measure, such the Euclidean distance, and ranked from 1 to k, where 1 is the closest and k the furthest.

The probability of choosing one block as the successor block is defined as:

$$P(j) = \frac{1/j}{\sum_{1=0,\dots,k} (1/j)}$$
(4.11)

where *j* is the location of the block in the ranking.

A simple example of the method with random numbers is represented in Table 4.1 and 4.2 where *d* is equal to 2. The Euclidean distance is reported in the second column and it is calculated between the blue highlighted blocks and the others. The numbers in the third column (x_{t+1}) are the next values selected according to such distances. Choosing *k* equal to 3, the closest distances are the ones highlighted in red. In the second table (below) the distances are ranked

X _t	Distance	X_{t+1}
5.54	3.33	2.74
6.83	3.62	5.86
2.74	6.16	5.32
5.86	3.50	3.69
5.32	4.33	4.57
3.69	5.5	5.34
4.57	4.58	8.58
5.34	2.98	7.77
8.58		
7.77		

Table 4.1: k-nn example procedure with random numbers - Calculation of the distances and identification of the next values.

knn	X_{t+1}	Rank(j)	P(j)		
2.98	7.77	1	0.55		
3.33	2.74	2	0.27		
3.50	3.69	3	0.18		

 Table 4.2: k-nn example procedure with random numbers - Ranking of the nearest neighbors.

with the associated probability P(j) according to equation 4.11. For the generation of the weather scenarios, *Rajagopalan and Lall* (1999) suggests to use one value instead of one block; in this way the weather on a given day depends only on the previous day's weather. One important shortcoming of the k-nn bootstrap is the inability of simulating values outside the historical range of observations. Moreover the k-nn generators tend to underestimate the lengths of wet and dry spells especially in situation with short spell lengths (*Apipattanavis et al.*, 2007).

4.2.3 Semi-parametric weather generators

In order to alleviate the limits of parametric and non-parametric generators, *Apipattanavis et al.* (2007) proposes a "hybrid" solution that combines the two approaches described before, implying first a Markov chain of precipitation occurrence and subsequently the k-nn bootstrap to simulate each day weather according to the chain.

This approach is called semi-parametric weather generator and it is applied in the present study to generate scenarios of temperature and precipitation for the Red River streamflow basins (Da, Gam, Lo, Chay, and Thao). An important benefit of this method is the possibility of keeping the spatial correlation among multiple sites.

Historical temperature and precipitation of each sites were averaged according to their basin area to generate a first order Markov chain. Three possible states

Month	P(D)	P(W)	P(EW)	P(D D)	P(D W)	P(D EW)	P(W D)	P(W W)	P(W EW)	P(EW D)	P(EW W)	P(EW EW)
Jan	0.692	0.170	0.138	0.816	0.128	0.057	0.315	0.662	0.023	0.532	0.460	0.008
Feb	0.692	0.170	0.138	0.475	0.201	0.324	0.094	0.600	0.306	0.067	0.659	0.274
Mar	0.558	0.303	0.138	0.530	0.000	0.470	0.649	0.000	0.351	0.685	0.000	0.315
Apr	0.285	0.572	0.143	0.777	0.196	0.027	0.420	0.580	0.011	0.620	0.372	0.007
May	0.108	0.747	0.145	0.413	0.153	0.434	0.028	0.535	0.437	0.144	0.690	0.166
Jun	0.043	0.823	0.134	0.545	0.000	0.455	0.774	0.000	0.226	0.536	0.000	0.464
Jul	0.012	0.839	0.149	0.728	0.227	0.045	0.000	1.000	0.000	0.734	0.259	0.007
Aug	0.031	0.823	0.146	0.409	0.223	0.368	0.012	0.829	0.159	0.311	0.299	0.390
Sep	0.107	0.751	0.142	0.548	0.000	0.452	0.670	0.000	0.330	0.500	0.000	0.500
Oct	0.228	0.621	0.151	0.532	0.450	0.018	0.324	0.676	0.000	0.860	0.115	0.024
Nov	0.489	0.413	0.098	0.205	0.363	0.431	0.023	0.720	0.257	0.477	0.207	0.316
Dec	0.722	0.161	0.118	0.669	0.000	0.331	0.606	0.000	0.394	0.525	0.000	0.475

Table 4.3: Unconditional and Transition probabilities of dry (D), wet(W), and extremely wet (EW) *days*.

are considered: dry (D), wet (W), and extremely wet (EW). A dry day occurs when the precipitation is less than 0.33 mm, an extremely wet day when the precipitation is greater than the 80th percentile of daily amounts for the simulated month, and a wet day when the amount of rain is between the dry and extremely wet thresholds.

As the first step, from the historical observations, we have calculated the probabilities of each state and the transition probabilities from one state to another independently for each month to capture the seasonality (see equations 4.5 and 4.6). The probabilities are reported in Table 4.3.

The Markov chain simulation was carried out as follows:

- 1. Uniform random numbers in the interval [0,1] U_i , i = 1, ..., N are generated;
- 2. Starting, for example, from January, if U_1 is less than 0.692, the first day is dry; if it is between 0.692 (sum of P(D) and P(W)) and 0.862, it is wet, and extremely wet otherwise;
- 3. The second day is generated considering the first day, U_2 and the transition probabilities. For example, if the first day is classified dry and U_2 is lower than 0.816, the second day is also dry because in January the probability of having a dry day after a dry one is 0.816 (see Table 4.3);
- 4. The third step is repeated until the end of the desired length series, changing the probabilities when the monthly boundaries are crossed;

A forty years Markov chain was generated according to the monthly probabilities. Once we got a sequence of precipitation states, the k-nn bootstrap with d = 1 is applied to generate temperature and precipitation sequences for each basin:

1. The same random number is selected from the historical period and the Markov chain simulation (x_t) , for example the 1st day of May. The day

selected and the next one are associated to a state (D,W and EW), for example 1st is wet, 2nd is dry;

- We select a 7-day window centered in the 1st of May (from the 28th of April to the 4th of May) and search a sequence "wet day/dry day" in the same window of the historical observations;
- 3. We compute the Euclidean distance between x_t and all the first days of the sequence pairs selected in step 2, called "neighbors";
- The values are ranked from the lowest to the largest distance and *k* neighbors are selected. *k* is chosen as the square root of the number of neighbors (*Lall and Sharma* (1996));
- 5. The probability defined in equation 4.11 is associated to each neighbor;
- 6. A random number between 0 and 1 is generated. If that number is included in the probability interval of a neighbor, that neighbor is selected as the next value.
- 7. Starting from the newly generated value, step 2 to step 6 are repeated to generate weather for the next days.

At this point, the generated scenarios of temperature and precipitation are just a resampling of the historical records. In order to understand how the system works with climate changes, we applied the additive and multiplicative factors introduced in the previous section to different scenarios generated with the semi-parametric approach. We produced 40-year scenarios for each subcatchment (Da, Lo, Thao, Gam, Chay), by varying the temperature and by modifying the precipitation, for a total of 56 possible future climate. Applying first the semi-parametric approach and then the additive and multiplicative perturbations, the resulting scenarios are different from the history not only in terms of mean but also in terms of inter annual variability.

4.3 Hydrological model

The generated scenarios of temperature and precipitation (t^H , p^H) are used as inputs for the generation of the streamflow for each sub-basin. This step requires using an hydrological model and the HBV model was employed. The Hydrologiska Byrans Vattenbalansavdelning (HBV) model (*Bergström*, 1992) is a semi distributed conceptual rainfall-runoff model developed for operational

flood forecasting in Sweden. The model uses sub-basins as primary hydrological units where the basins are geographically and climatologically heterogeneous. It is composed by four storage units and it relies on five state variables: soil water storage, snow store, depth of liquid in the snow store, soil storage for shallow and deep layer. The model takes as inputs temperature *T* and precipitation *P* and it returns as output the discharge Q_{sim} .

In Figure 4.3, a scheme of the model is represented, while state variables and parameters are listed in Table 4.4 and 4.5 respectively.



Figure 4.3: *HBV model: storage elements are gray shaded, model states and model parameters are shown in blu and red, respectively.*

State	Description
sowat	soil water storage
sdep	snowstore
ldep	depth of the liquid in the snow store
stw1	soil storage - shallow layer
stw2	soil storage - deep layer

Table 4.4: HBV state variables.

4.4. Agricultural water demand generation

Parameter	Unit	Description
<i>K</i> ₂	[day]	withdrawal rate from deep layer
<i>K</i> ₁	[day]	withdrawal rate from deep layer
K ₀	[day]	withdrawal rate from shallow layer (interflow)
MaxBas	[hour]	length of hydrograph routing transformation
degd	[mm/day C]	degree day factor (snowmelt rate)
degw	[C]	base temperature above which melt occurs
ttlim	[C]	temperature threshold below which freezing occurs
perc	[mm/day]	percolation rate into deep layer
β	[-]	distribution of soil stores
lp	[-]	limiting soil moisture at which PET take place
F _c ap	[mm]	maximum soil moisture storage
hl1	[mm]	maximum shallow layer storage

Table 4.5: *HBV parameters*.

The HBV-light software developed at the University of Zurich by Jan Seibert (*Seibert and Vis*, 2012) was used in this work.

For the calibration, the software takes as input, historical precipitation, temperature, and streamflow data and it returns the parameters with the related R^2 , which gives an idea of how good the model describes the system dynamics. The calibration was performed over a 40-years dataset.

The parameters' calibration for the five basins involved in the study provides good results as shown in Table 4.6 .

Catchment	R^2 - Calibration	R^2 -Validation			
Da	0.89	0.88			
Thao	0.86	0.83			
Chay	0.82	0.75			
Lo	0.83	0.79			
Gam	0.88	0.87			

Table 4.6: Performance of the HBV parameters' calibration and validation.

All the combinations of temperature and precipitation scenarios were simulated on the HBV model obtaining 56 scenarios of 40-years streamflow for the 5 sub-catchments. For the simulation, each temperature scenario was combined with the corresponding evapotranspiration, which was calculated through the equation of Thornthwaite (*Thornthwaite*, 1948).²

4.4 Agricultural water demand generation

The water demand from the agricultural sector (W^A) represents the largest contribution to the total demand. It is calculated through the software CROPWAT,

²The Thornthwaite equation assumes the mean monthly evaporatranspiration depends only on the daily temperature and the latitude of the area of interest.

Irrigation zone	Rainfall station	Meteorological station
Tich-Thanh Ha	My Durc	Son Tay
Nhue	Tuong Tin	Hanoi
Right Day	Phu Ly	Phu Ly
6 pumping stations	Phu Ly	Phu Ly
North of Ninh Binh	Nho Quan	Ninh Binh
South of Ninh Binh	Ninh Binh	Ninh Binh
Central Nam Dinh	Van Ly	Nam Dinh
South of Nam Dinh	Van Ly	Nam Dinh
North of Thai Binh	Thai Binh	Thai Binh
South of Thai Binh	Thai Binh	Thai Binh
Downstream of Thai Binh River	Kinh Mon	Chi Linh
Bac Hung Hai	Thai Binh	Hai Duong
North Duong River	Thai Binh	Son Dong

 Table 4.7: Irrigation zones with related rainfall and meteorological stations of the Red River delta

developed by the Land and Water Development Division of FAO. The model takes as inputs rainfall, meteorological, soil, and crop data and gives as output the monthly irrigation requirement.

For the calculation of the demand, the Red River delta was divided in 13 areas. Each irrigation zone is associated to a rainfall station and a meteorological station (Table 4.7), which provide the data needed for the calculation.

The climate data required are monthly cumulated precipitation, average temperature, humidity, wind speed, and solar radiation. For the generation of the demand scenarios, historical climate data of temperature and precipitation were generated as described in section 4.1. Finally, CROPWAT requires also a crop pattern which is a list of crop types and the percentage area cultivated with each crop. The Red River delta is mainly cultivated with rice, maize, potatoes, and oranges. We used the same crop distributions.

The calculation of the water needed to irrigate the crops (*IRR* [mm/day]) is based on the water balance equation

$$IRR = ET_c + LP_{rep} + P_{rep} - P_{eff}$$

$$(4.12)$$

Where ET_c [mm/day] is the surface evapotranspiration and it is calculated as:

$$ET_c = ET_0 * K_c \tag{4.13}$$

The potential evapotranspiration ET_0 is estimated from the climate data using the Penman-Monteith equation while K_c is the crop coefficient depending on the crop type and the crop growing stages. The other components of the water balance equation are the amount of soil water LP_{rep} [mm], the stability of

4.5. Non agricultural water demand generation

Invigation mana	Aquaculture	Industries	Urban pop	Town pop	Rural pop	Cow	Pig	Poultry
Imgation zone	[ha]	[ha]	[people]	[people]	[people]	[animals]	[animals]	[animals]
Tich Thanh Ha	3336	2426	0	129500	1226800	125155	690968	6395804
Nhue	5908	1574	2062700	89843	1626750	44411	591790	5787805
Righ-day	288	30	0	2232	43577	2772	25242	277873
6 Pumping Station	5987	1003	246125	40745	958638	57172	529948	3920507
North of Ninh Binh	442	148	0	6374	178677	21965	84446	647620
South of Ninh Binh	5021	732	87002	65547	626315	43903	287851	2746907
Central Nam Dinh	4174	70	0	60483	564279	11846	240309	1777679
South of Nam Dinh	8325	0	0	58178	733574	7207	288558	2134604
North of Thai Binh	5794	292	20800	48000	976800	45360	601400	5079400
South of Thai Binh	4004	994	83200	20000	712200	24240	425600	2882600
Downstream of Thai Binh	21594	2965	559800	342306	1846021	50747	793580	8311083
Bac Hung Hai	2886	2451	91541	100919	848998	57684	377910	3943000
North of Duong River	14254	2811	415357	191218	2320015	96469	1104534	11605567

Table 4.8: Historical values of the water consumption sectors

ground water P_{rep} and the effective rainfall P_{eff} [mm].

The agricultural demand was calculated under each combination of temperature and precipitation scenarios, obtaining 56 different values of irrigation requirement. The resulting crop demand in [mm/month] related to each irrigation zone is multiplied by the area of the district to get the monthly volume m^3 and distributed over the year to obtain the daily values (*WA*).

4.5 Non agricultural water demand generation

The scaling factors (Δ^W) for the non-agricultural water demand, sampled as described in section 4.1, are employed in the generation of demand scenarios (W^{NA}). We consider the same partition of the delta into 13 districts as for the agricultural demand. For each district the historical values of the water sector are reported in Table 4.8.

The calculation of the water demand is performed using a simple model.

 W^{NA} = water consumption sector × standard of water use (4.14)

The water consumption sector is multiplied by a "standard of water use", which provides the amount of water needed for each sector unit. The values of these standard for the different sectors are reported in Table 4.9 and 4.10. The Vietnamese institution provide yearly standard values for all sectors except for aquaculture which require different monthly values.

The standard are multiplied with the scaling factors (Δ^W) and converted in daily values to obtain 100 different scenarios of daily demand. In order to keep the correlation between districts, we assumed the same pattern in terms of socio-economic changes. Therefore, for each scenario, the water consumption sectors from different districts are multiplied by the same scaling factors.

Water consumption sector	Standard of water use	Unit
Industries	128	m3/day/ha
Urban population	343	1/day/person
Town population	257	1/day/person
Rural population	115	1/day/person
Buffalo, cow	65	l/day/animal
Pigs	15	l/day/animal
Poultry	1	l/day/animal

 Table 4.9: Standard of water use

	Aquaculture Standards - m ³ /ha/month										
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	1333	1713	1713	1714	1714	0	0	0	1714	1714	1714

Table 4.10: Standard of water use - Aquaculture

Each agricultural demand scenario is added to each non-agricultural demand scenario for a total number of demand scenarios (W^{TOT}) equal to 5600. Finally, the water consumption for environment is also considered. It is the amount of water used for the dilution of waste water used for crops, livestock, people, industry, and fisheries. In Vietnam there is no standard and the water requirement for environment is assumed equal to 10% of the total demand, which is added for each scenario generated. We assumed that this percentage doesn't change in future.

4.6 Sensitivity Analysis

The resulting objectives are analyzed via Delta Sensitivity Analysis (SA) method. SA is defined by *Saltelli* (2002) as the study of how *"uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input"*. In the present study, SA helps in the identification of the input variables that cause relevant changes in the system performance.

Many works on SA propose variance-based methods (e.g. *Satelli et al.*, 2000; *Sobol*, 2001; *Rabitz et al.*, 1999) in which the output variance is attributed to the uncertainty of the inputs. The drawback of this approach is that it implicitly assumes that the variance is a sufficient indicator of the output variability.

A possible solution to mitigate this shortcoming is the Delta SA (*Borgonovo*, 2007). The Delta approach is a global SA method. It is defined as moment-independent since it considers the entire distribution of the model inputs and output for the evaluation of the sensitivity indicator δ . The process to calculate δ is the following:

$$s(X_i) = \int |f_Y(y) - f_{Y|X_i}(y)| dy$$
(4.15)

$$E_{X_i}[s(X_i)] = \int f_{X_i}(x_i)[s(X_i)] dx_i$$
(4.16)

$$\delta_i = \frac{1}{2} E_{X_i}[s(X_i)] \tag{4.17}$$

Where X_i is one input parameter and Y is output. $E_{X_i}[s(X_i)]$ is the expected shift between $f_Y(y)$ and $f_{Y|X_i}(y)$. They are respectively the Y-density function and the conditional density of Y given that one parameter X_i assumes a fixed values. A visual representation of the shift between the two distribution is shown in Figure 4.4.



Figure 4.4: *The shaded area represents the shift between* $f_Y(y)$ *and* $f_{Y|X_i}(y)$

The value δ_i represents the normalized expected shift in the distribution of the output *Y* provoked by the input parameter X_i . This indicator can assume values between 0 and 1. *Y* is independent from X_i if δ is equal to zero. The higher is the values of δ , the more the current parameter is influencing the model output.

We applied this approach to the Red River system performance employing as inputs all the variables perturbed for the scenario generation, such as temperature, precipitation, streamflows, and each water demand component in order to identify the most important factors which may alter the performance of the system operations, particularly in terms of water supply.

4.7 Superimposition of climate projections

As the final step of the study, we contrasted the performance under the generated scenarios and the performance under an official projection form the IPCC fifth assessment report. According to the Top-Down method, described in section 2.1, we considered the scenario RCP 8.5, which represents a future with no mitigation and no emission reduction. This represents on of the worst case conditions and a useful reference for the bottom up generated scenarios.

Data of temperature and precipitation dynamically downscaled from the GCM to the RCM were downloaded from CORDEX (COordinated Regional climate Downscaling EXperiment) East Asia. Particularly, we chose temperature and precipitation data downscaled from the GCM HadGEM2-AO to the RCM Had-GEM3-RA from the NIRM institute³. The time series were downloaded for an historical period (1996-2000) and for projected period between 2041-2050. Climate data are distributed as NetCDF files, where the time series is split in 5-years blocks and organized over a discretized spatial domain with a resolution that depends upon the specific climate model.

However, RCM output are generally still unsuitable for estimating local impacts and can be further refined via statistical downscaling techniques. In this work, the Quantile Mapping (*Déqué*, 2007) is used. This method is based on the correction of the RCM distribution shape that is fitted with the observed data distribution. The process needs as inputs the historical RCM data, called control, and the observed data. We take as an example the temperature in the Da basin to explain the process steps. In Figure 4.6 we plotted control and observed data (left), and their cumulative distribution functions (CDF) (right). The quantiles of the two distribution are plotted against each other in the so called Q-Q plot which is a graphical method for comparing two probability distributions (Figure 4.7). Using the correction function, the quantiles of the two distribution can be matched, and the same function can be used to correct the scenario time-series.

In Figure 4.8 the scenario downscaled is represented to confirm that the method successfully corrected the RCM output distribution to reproduce the local observations.

³National Institute of Meteorological Research, South Korea



Figure 4.5: Difference between historical RCM outputs and observed data in the Da basin.



Figure 4.6: Difference between the CDFs of the historical RCM outputs and observed data in the Da basin).



Figure 4.7: *Q*-*Q plot representing the quantiles of the control against the observation.*



Figure 4.8: *Scenario downscaled using the Q-Q plot.*

The same process has been applied to temperature and precipitation of each

basin. We used these downscaled scenarios of temperature and precipitation to simulate the HBV model and obtain the sub-catchment streamflows. The mean increase in temperature and precipitation with respect to the historical period was used in the calculation of the crop irrigation requirements in the Red River delta using CROPWAT model. The water demand for the other consumption sector, instead, was directly taken from the scenario built by Vietnamese institutions within the IMRR project (Report D6.1) named "high scenario 2050". This scenario represent a combination of increasing aquaculture, industries, and population demands.

5

Results and discussion

In this section, the numerical results are presented following the same workflow described in section 4. First of all, the results from the scenario generation are illustrated, particularly for weather, streamflow, and demand. Subsequently, the system performance obtained by the simulation of the Red River model is analyzed and discussed. Finally, we contrast the performance obtained with the generated scenarios and the one calculated with the IPCC projection.

The simulation of the historical system's operations is approximated by selecting a compromise solution from the Pareto optimal set designed via EMODPS (see section 3.4). Each optimization was run for 2 million function evaluations. The Pareto optimal policies were obtained from the results of 20 random optimization trials to improve the solution diversity and avoid dependence and randomness.

Figure 5.1 shows the Pareto optimal policies over the historical period (1990-2010), where the flood damages and hydropower objectives are plotted on the primary axes and the water deficit is represented by the dimension of the circles. The compromise solution was chosen by adopting the Utopia criterion. It considers the difference between the solutions and the absolute optima of the three objectives.

Performances of the compromise policy are: $J^{hyd} = 60 \text{ (GWh/d)}$, $J^{flood} = 7918.2$ (-), and $J^{supply} = 30 \text{ (m}^3/\text{s})^2$. To identify the system vulnerabilities with respect to the co-varying climate and socio-economic forcing, the selected policy is evaluated via simulation over 224000 scenarios, obtained as a combination

of 56 climate, 40 hydrological years, and 100 socio-economic scenarios.



Figure 5.1: Set of Pareto optimal policies

5.1 Weather generation

Temperature and precipitation scenarios of a 40-years period were generated using the semi-parametric approach combined with the additive and multiplicative perturbation (section 4.2). We choose the Da basin for the result representation as it is the largest and most influencing basin. Daily temperature and precipitations averaged on the basin are shown in Figure 5.2 and 5.3 respectively for a three-years period, where each color line represents a series produced applying different Δ^T (or Δ^P) on the resampled values. The black line, instead, represents the historical records from 1961 to 1963. The Da basin is chosen for the result representation as it is the largest and most influencing basin.

Not surprisingly, in both figures the produced scenarios successfully follow the seasonal pattern of the historical data. Temperature series show the same timing for positive and negative peaks as in the past and precipitation series well reproduce the monsoon season between May and October. While in the temperature graph it is easy to distinguish the differences in the mean perturbation of each scenario, for precipitation it is more complicated due to the strong variability of the rainfall amount between consequent days. The advantage of using a semi-parametric approach can be stressed by looking at the temporal behavior of the generated series, which show differences not only in their mean

but also in the inter-annual variability, composed by time shiftings and different amounts in the extreme events.

Another important feature achieved by using this weather generator is the capability of preserving the spatial correlation between basins. In Figure 5.4 and 5.5, the spatial correlation across the Red River basins is shown for temperature and precipitation respectively, comparing the historical correlation and the generated one. The historical correlations appears to be preserved in both cases, even though the correlation related to precipitation is lower due to its higher variability.



Figure 5.2: Temperature scenarios generated compared to the historical data (1961-1963) in the Da basin.



Figure 5.3: *Precipitation scenarios generated compared to the historical data (1961-1963) in the Da basin.*

5. Results and discussion



Figure 5.4: Spatial correlation in temperature among the sub-basins, for the historical period (left) and the generated scenario (right).



Figure 5.5: Spatial correlation in precipitation among the sub-basins, for the historical period (left) and the generated scenario (right).

5.2 Hydrological model

Temperature and precipitation scenarios are the inputs of the hydrological model (HBV), which provides an estimation of the basin streamflows. We run the model over all the combinations of temperature and precipitation obtaining 56 scenarios. We considered the 40 years generated as singles indipendent annual scenarios to show the system response to different hydrological inter-annual

variabilities.

To visualize the resulted streamflows we calculated the cyclostationary average over a 5-year period to filter the single annual behaviors of the streamflows. Moreover, we fix one of the two drivers (i.e. temperature and precipitation) while the other one can vary in its range. In Figure 5.6, the daily streamflow scenarios are obtained with a Δ^T equal to $+3^{\circ}C$ while Δ^P varies from -20% to +60%. In Figure 5.7, instead, we made the temperature change from $-2^{\circ}C$ to $+5^{\circ}C$ while the Δ^{P} was set at +20%. Both figures are compared with the cyclostationary average of the historical streamflow between 1961 and 1966 represented by the black line. In both cases, the generated streamflows for the Da basin reflect the seasonal variability of the historical pattern, particularly in the monsoon season. In the first figure, the highest peak (dark blue line) shows an increase of about 60% compared to the highest peak of the historical record. On the other hand, the scenarios associated with the precipitation decrease causes a decrease in the highest peak of about 50%. As it was expected, the main driver causing relevant changes in the streamflows amount and timing is the precipitation. It is highly visible in the figures that varying the precipitation variable affects the streamflow pattern way more than just varying the temperature within the basin. When a Δ^T is applied on the scenarios (see Figure 5.7), the differences in values are caused by the changing in evaporation which barely affect the streamflow amount. The evaporation increase is due to higher temperature that causes lower values in the streamflows.

The same approach is applied to all the streamflow basins from Figure 5.8 to 5.15. It is easy to notice the high variability of the scenarios generated that will allow to test the system under a wide range of streamflows. The variability is visible in both amount and timing, sometimes resulting in an anticipation of the monsoon season in May (e.g. Figure 5.8). A global overview of the streamflow is obtained using the parallel axis plot in Figure 5.16. The lines represent each scenarios by crossing the axes at their values of each variable reported on the top. This graph confirms that the yearly average streamflow depends mostly on the precipitation. The historical values are still represented by the black line. The spatial correlation is preserved also in the streamflows of different sub-catchments as it is shown in Figure 5.17. The correlation measure between the Chay basin and the others appears to be lower, especially in the historical period. Chay is the river characterized by the smallest flow and it is the only inflow to the system that doesn't rise in China.



Figure 5.6: *Streamflow scenarios obtained by varying the precipitation scaling factors in the Da basin.*



Figure 5.7: Streamflow scenarios obtained by varying the temperature scaling factors in the Da basin.



Figure 5.8: Streamflow scenarios obtained by varying the precipitation scaling factors in the Gam basin.



Figure 5.9: Streamflow scenarios obtained by varying the temperature scaling factors in the Gam basin.



Figure 5.10: Streamflow scenarios obtained by varying the precipitation scaling factors in the Lo basin.



Figure 5.11: Streamflow scenarios obtained by varying the temperature scaling factors in the Lo basin.


Figure 5.12: Streamflow scenarios obtained by varying the precipitation scaling factors in the Thao basin.



Figure 5.13: Streamflow scenarios obtained by varying the temperature scaling factors in the Thao basin.



Figure 5.14: Streamflow scenarios obtained by varying the precipitation scaling factors in the Chay basin.



Figure 5.15: Streamflow scenarios obtained by varying the temperature scaling factors in the Chay basin.





Figure 5.17: Spatial correlation in the streamflow among the sub-basins, for the historical period (left) and the generated scenario (right).

5.3 Agricultural water demand generation

The agricultural water demand is estimated by simulating temperature and precipitation scenarios with Cropwat in the 13 irrigation districts of the river delta. The resulting irrigation requirement is represented in Figure 5.18, where the primary axes are the variation in temperature (x-axis) and precipitation (y-axis), while the total water needed to irrigate the crops is shown on the colorbar. As it was expected, there is a clear gradient of water demand when moving from the top-left to the bottom-right corner of the figure. The maximum increase in temperature and the maximum reduction in precipitation leads to the highest water demand. Conversely, lower temperature and high precipitation generates the minimum demand.

5.4 Non-Agricultural water demand generation

The demand from the other consumption sectors is calculated through a Latin Ipercube Sampling of scaling factors to be multiplied to the historical consumption sectors. In Figure 5.19, the 100 scenarios of demand are shown using a parallel axis plot. The axis represent the percentages used for scaling each socio-economic consumption sector except for the last one that shows the resulting annual demand.

The figure shows that the Latin Ipercube method allows to produce a sampling that covers uniformly the input ranges. However, the high number of scenarios



Figure 5.18: Total irrigation requirement (m^3/y) for the different combination of temperature and precipitation factors.

and their different patterns make the graph difficult to analyze. Therefore, in order to understand which sector most influence the increase in demand, starting from the last axes, we isolated the scenarios causing the highest and lowest values of the total demand, shown in Figure 5.20 and Figure 5.21 respectively. The sectors that most influence the total demand appear to be aquaculture, industries, urban, and town population since their changes produce the similar alterations in the total demand. Rural population and livestock, on the other hand, have a lower impact on the resulting total water requirement. This is probably due to the lower standard of water use associated to different sectors, such as for example to rural population compared to the urban or town ones (see Table 4.9). This difference can be also attributed to the largest scaling factors of industries and town population associated to the fast-developing Vietnam society (see Figure 4.2).











5.5 Simulation of the Red River model

All the combinations of the scenarios presented in the previous sections were simulated with the Red River model to obtain the resulting system performance in terms of hydropower production, flood damages, and water supply deficit. Due to the extremely high number of simulations, the result visualization is very complex and difficult to interpret. For this reason, we decided to start discussing the results separating them on the basis of the different family of scenarios used in the simulation.

First of all, the hydrological variability is analyzed. For each climate exposure, indeed, we simulated 40 scenarios of one year . The differences among the 40 scenarios represent the hydrological inter-annual variability under the same climate.

Figure 5.22 shows the variability in the streamflows for the different basins for a fixed $\Delta^T = +3^{\circ}C$, $\Delta^P = +20^{\circ}$. On the last three axes we plotted the system performance composed by: the hydropower production in GWh/day, the supply deficit in $[m^3/s]^2$ and the flood objective [dimensionless]. On the axes, the descent direction leads to the optimal performance for all the objectives (J^{hyd} values are presented with a minus sign because the objective vector have to be minimized, while our aim is to maximize the hydropower production). Even thought the objective variability range is narrow, the parallel axis plot highlights the capability of the generated scenarios to produce differences in the resulting performance.

The climate variability is another key aspect of the present analysis, where we consider 56 combination of temperature and precipitation scenarios which produce changes in the streamflow and in the agricultural demand. In Figure 5.23, the effects of the climate variability on the crop requirement, supply deficit, hydropower production and flood damages are illustrated. Each climate exposure is associated to an ensamble of 40 streamflow scenarios. In order to have a simple visualization of the results and filter the hydrologic variability discussed in Figure 5.22, the 40 objective values related to each simulation are averaged.

Results show that the water demand from agriculture is mostly related to the amount of precipitation. When the precipitation is highly increased (i.e. blue lines), the main consequences are high hydropower production, along with low demand and supply deficit. Flood damages, instead, are penalized by increasing precipitation. This trade off among the objectives in well visible from the parallel plot. The lines are approximately parallel among demand, deficit and hydropower. They, instead, invert the pattern when flood is concerned.

The last variability refers to the socio-economic sector. It is represented by plotting the water consumption sectors and the resulting supply deficit in Figure 5.24. As in Figure 5.22, the climate, and consequently streamflow and agricultural demand, are fixed. The supply objective is averaged over the 40 hydrological scenario realizations. The parallel pattern of the lines between the total demand and the objective J^{supply} demonstrates the strong dependency of the objective on the socio-economic demand. Consequently, the factors that most influence the demand are also highly responsible for changes in the supply deficit.

Lastly, the full ensemble of scenarios is examined. In Figure 5.25 all the variables perturbed for generating the scenarios are plotted on the vertical axes. Particularly, all the combination of climate and demand are plotted (5600 lines), while, as in Figure 5.23, the objectives are averaged across the 40 years representing the hydrological variability.

Starting from the left side, there are temperature and precipitation factors that cause changes in the annual agricultural demand (WD-AGR) and in the mean daily streamflows (DA, GAM, LO, CHAY and THAO). On the following axes, all the water consumption sectors are shown and they are added together in the annual non-agricultural demand (WD-NA). The total demand (WD-TOT) is the sum of the agriculture and the other sector requirements. Finally, at the end of the graph, the resulted three objectives are represented.

A number of trade offs emerges from the parallel plot visualization. First of all, the pattern among the agricultural requirement and the streamflows is inverted. The lower is the precipitation and therefore the streamflow, the higher will be the demand. In the water consumption sectors the predominant color is blue only because all the combination of demand and climatic variability are overlapped. The supply deficit is nearly directly proportional to the total demand and indirectly proportional to the streamflows. The flood damages and the hydropower production, instead, have completely different behaviors, as was already discussed in Figure 5.23.













5.6 Quantifying the vulnerabilities of the historical system management

In order to highlight the vulnerabilities of the system management, we reduce the number of realizations on Figure 5.25 by isolating the scenarios that show a degrading performance with respect to the historical one. This is illustrated in Figure 5.26 for floods, in Figure 5.27 for hydropower production and in Figure 5.28 for supply deficit, respectively.

From the figures we have the possibility to distinguish which scenarios might be critical for the system. The flood damages (Figure 5.26) are mostly influenced by an increase in the precipitation, particularly the objective values get worse when the rainfall is increased by more than 30%. It is, instead, almost independent from temperature and demand. The colors highlight that the hydropower production (Figure 5.27) shows the same pattern as floods, but the degrading performance is caused by the opposite perturbation in precipitation. In particular, around 2000 simulation exceeds the historical flood damages, and around 3000 simulations attain a hydropower which is lower than the obtained over the historical conditions. While for the last two objectives the number of vulnerable scenarios are around 2000 and 3000, for the supply deficit (Figure 5.28) this number grows to more than 5000. A very small number of realizations meets the historical values of the *J^{supply}* objective. They are the scenarios with very high values of precipitation, low temperature and low values of aquaculture and industry consumptions. The main causes are the alteration of the streamflows induced by the changing climate and the increasing water demand in the delta. In particular, the large increase of the non-agricultural demand associated to the fast-developing Vietnamese society produces an increase in the total demand during the entire year, thus challenging the water supply strategy designed over historical conditions characterized by low demands in the winter period (e.g. December, January).

This result highlights the need of adapting the system management to account for the future economic development and demographic growth.









5.7 Sensitivity Analysis

The visual analysis of the results could be not enough to understand the main vulnerabilities for the system performance. Therefore, in this section we propose to analyze the results illustrated in Figure 5.28 by means of a Sensitivity Analysis. We focused particularly on the supply deficit objective since our analysis is mostly related to the water demand sectors and their influence on the system performance. The inputs we used in the SA are the 224,000 scenarios of temperature, precipitation, streamflows, agricultural and non-agricultural demand. The outputs employed in the analysis are the vector of 224,000 values of supply deficit resulted from the simulation of the Red River model over these scenarios.

The bar plot in Figure 5.29 shows the input variables ranked by the values of the sensitivity index δ . The index, described in section 4.6, can be interpreted as a measure of the importance of the input in causing changes in the output. On each column, the 95% confidence interval is reported, calculated by multiplying the δ "confidence", which represents the standard deviation of the index, by 1.96, which is approximately the value of the 97.5 percentile. Although the



Figure 5.29: Delta index calculated between the system input variables and the supply deficit J^{supply}.

differences between the indices is sometimes small, the variable ranking can be explained as follows:

- The agricultural demand is the main driver which provokes changes in the supply deficit. This result was expected since agriculture is the most important sector and contributes 58% of the total demand.
- The demand from agriculture is followed by the availability of water, rep-

resented by the streamflows. In particular, Thao and Lo rivers have large values because they are natural rivers, not regulated by dams, while the Da river represents the largest contribution to the total flow. The Chay river has, instead, the lowest influence since it provides the smallest flow contribution to the streamflow reaching the Red River delta.

- The temperature appears to be relevant and, interestingly, it influences the system more than precipitation. This is probably due to the two-fold effect of temperature on the hydrological process and on the agricultural water demand, while precipitation is strongly correlated with streamflow. In the global warming context, in which temperature increase is one of the main implications, this result has to be considered for identifying candidate adaptation options.
- Regarding the water consumption sectors, the indices reflect the results of the visual analysis of section 5.4: industries and aquaculture are the most influencing components, followed by population and livestocks.

5.8 Superimposition of climate projections

In this section we present the results from the last step of the bottom-up approach, the superimposition of the climate projections downscaled with the quantile mapping method (see section 4.7). Before implementing the statistical downscaling of the climate variables, we plotted the dynamical downscaled temperature and precipitation to have an idea of the spatial distributed expected change. Figure 5.30 shows the average annual temperature in 2000, 2050, and 2100.

The expected increase in temperature is well visible from the snapshots and it is particularly high in the delta region.

After implementing the quantile mapping we calculated the annual mean values of temperature and precipitation in 2050 and 2100 in the different subbasins of the Red River system. The projected values are compared with the historical period to have an idea of the expected change. The results in table 5.1 and 5.2 suggest a mean increase in temperature of about 1.2° C by 2050 and 3.6° C by 2100. For precipitation, on the other hand, the expected increase is around 6% by 2050 and 30% by 2100. We selected the period between 2041 and 2050 for the comparison with the generated scenarios.



Figure 5.30: Dynamically downscaled RCP8.5 values of temperature in 2000, 2050, 2100.

Sub-catchment	historical (1991-2000)	RCP8.5(2041-2050)	difference	RCP8.5 (2091-2100)	difference
Da	18.95	20,11	1.16	22.39	3.44
Gam	19.22	20,89	1.67	23.62	4.4
Lo	18.05	19,24	1.19	21.54	3.49
Thao	17.49	18.51	1.02	20.7	3.21
Chay	20.07	21.23	1.16	23.75	3.68

Table 5.1: Comparison among mean temperature data (°C) downscaled in the historical period and in the future under the projection of the RCP8.5.

Sub-catchment	historical (1991-2000)	RCP8.5 (2041-2050)	difference	RCP8.5 (2091-2100)	difference
Da	4.15	4.34	4.58%	5.38	29.64%
Gam	4.18	4.32	3.35%	4.43	5.98%
Lo	3.74	3.92	4.81%	4.47	19.52%
Thao	3.7	3.908	5.62%	5.45	47.30%
Chay	3.05	3.41	11.80%	4.46	46.23%

Table 5.2: Comparison among mean precipitation data (mm/day) downscaled in the historical period and in the future under the projection of the RCP8.5.

The streamflow scenario obtained with the simulation of the downscaled climatic variables on the HBV model is shown in Figure 5.31. The highlighted color line represents the annual average projected streamflows. It appears to be within the range considered for the synthetic generation.

The hydrograph of the Da river streamflow scenario is illustrated in Figure 5.32 and compared with the other scenarios generated by perturbing the precipitation while Δ^T fixed at +1°*C*, which represents the closest increase in temperature to the RCP8.5 projection.







Figure 5.32: Annual behavior of the streamflow scenario resulted from the simulation of the IPCC projections with the HBV.



Figure 5.33: Superimposition of the demand scenario resulted from the simulation of the IPCC projections with CROPWAT.

The annual pattern of the Da basin streamflow appears to be characterized by lower peaks than the generated scenarios and the historical record, particularly in the monsoon season. The annual average increase calculated in table 5.2 doesn't account for this variability which is, instead, crucial in the objective calculation.

The same process is applied on the projections of the agricultural and nonagricultural demands provided by the Vietnamese institutions. The superimposition of the projections is represented in Figure 5.33 and 5.34.

These "official" projections are finally superimposed over results obtained over the synthetically generated scenarios (Figure 5.35). The results in Figure 5.35 show that:

- The flood damages objective performs better with the projected scenario. The objective values is under the one obtained with the historical period with the compromise policy ($J^{flo} = 7918$). This is probably due to the lower streamflow peaks shown in the streamflow annual behavior in Figure 5.32 that don't cause extreme events in the city of Hanoi.
- The same effect is observed in the hydropower production performance, which is, instead, degraded by the lower amount of streamflows coming from the basins under the IPCC scenarios.
- The supply deficit simulated with the projected scenario appears to be still higher than the optimal performance over the history but it is lower than the majority of the performances obtained with the generated scenarios. An explanation for that can be discovered by looking at the water sectors. The values of the scenario related to the sectors that most influence the demand (i.e. Aquaculture) are lower than the generated ones. Town population and livestock, which were classified as less responsible for increases in the demand, show instead a large increase. The resulting total demand is consequently lower than most of the generated scenarios.

The superimposition of the official projections provides an idea of how narrow is the exploration of the scenario space provided by the Top-Down approach. The large ensemble of scenarios generated in the present study, instead, is able to show which conditions of climate and socio-economic change are critical for the system and need to be accounted for finding a robust operating policy able to manage the system in such uncertain conditions. Particularly, one scenario of water demand is not enough to model the possible future changes in the water consumption sectors. They are expected to show a large variation in the rapid changing Vietnamese society with the possibility to cause serious deficit in the Red River delta.









6

Conclusions and future research

The aim of this thesis is the assessment of how the Red River system performs under perturbed climate and society in order to account for future vulnerabilities caused by global warming and rapid economic and demographic growth. These vulnerabilities are identified through a bottom-up vulnerability analysis. Starting from the historical conditions, we altered the main climate and socioeconomic drivers of the system to generate an ensemble of 224000 scenarios. The Red River model has been simulated over all the generated scenarios, defined by the values of the three main objectives of interest (i.e. hydropower production, flood damages, and supply deficit). The semi-parametric weather generator, combined with the additive and multiplicative perturbations, allowed to produce synthetic time series of temperature and precipitation with variations in the mean and in the inter-annual pattern keeping the seasonal characteristics of the historical records. Moreover, the spatial correlation has been preserved among the Red River basins.

The weather inputs has been used in the evaluation of the streamflow through the HBV model. The results show that the simulated streamflow mainly depend on the precipitation, while a variation in temperature doesn't produce significant changes.

The agricultural water requirement, which represents the largest contribution to the total demand, was estimated simulating the same additive and multiplicative factors on temperature and precipitation that are inputs for CROP-WAT model. Both variables appears to have strong impacts on the irrigation demand, which produce significant increases with growing temperature and decreasing precipitation.

Regarding the socio-economic sector, the water consumption from aquaculture, industry, population, and livestock, was perturbed through a factor sampling that allows to produce 100 scenarios associated to alternative plausible future societies.

The results from the simulation of the Red River model over the 224000 scenarios shows which conditions lead to a degradation in the system performance. As expected, hydropower production and flood damages are most influenced by the weather conditions, particularly by precipitation. The two objectives show inverted behavior while varying the rainfall amount which is the main driver causing changes in the streamflows.

The supply deficit, instead, is highly correlated to all the system inputs, thus representing the most vulnerable sector. Almost all the simulated scenarios present higher values of deficit compared to the one obtained under historical conditions. This result is due to the large variability of the generated demand scenarios and emphasizes the need of accounting for future demographic and economic changes in revising the historical system operations.

The last step of our analysis was the superimposition of the official projections, namely the RCP8.5 IPCC scenarios and the socio-economic projections provided by the Vietnamese institutions. This analysis highlights the possible decision biases associated to the traditional top-down approach, which considers only a limited number of scenarios and may significantly underestimate the vulnerabilities of the system when exposed to a wider range of plausible futures.

Further research may be conducted to improve the scenario generation, particularly for those related to the water demand. Regarding agriculture, rather than estimating only the irrigation requirement with CROPWAT, it would be interesting to evaluate the crop yield with a more advanced model (e.g. Aqua-Crop). In the delta context, where agriculture represents the most profitable economic sector, the yield would represent a better indicator of the farmers satisfaction. Another improvement could be achieved by using a more detailed model for the other water sectors. In the present study the scaling factors were generated almost randomly without considering that an increase in one sector could lead to a decrease in other one (e.g. urban and rural population due to internal migrations). However, the correlation between the sector variations should be involved in the study by developing a proper model that accounts for all the complex socio-economic dynamics.

Beside climate change and water demand increase, other factors should be included in the identification of the system vulnerabilities. Land use change, for example, with the associated erosion, leads to increases in the river solid transport that are already causing problems related to the higher river flow. Finally, the results of this work can be used to study the operational adaptive capacity of the system, namely how designing a new set of operating policies for the regulation of the four reservoirs in the basin allows adapting to the evolving conditions and increasing the resilience of the system.

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